Human Interfaces and Management of Information (HIMI) Challenges for "In-time" Aviation Safety Management Systems (IASMS)

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Abstract. The envisioned transformation of the National Airspace System to integrate an In-time Aviation Safety Management System (IASMS) to assure safety in Advanced Air Mobility (AAM) brings unprecedented challenges to the design of human interfaces and management of safety information. Safety in design and operational safety assurance are critical factors for how humans will interact with increasingly autonomous systems. The IASMS Concept of Operations builds from traditional commercial operator safety management and scales in complexity to AAM. The transformative changes in future aviation systems pose potential new critical safety risks with novel types of aircraft and other vehicles having different performance capabilities, flying in increasingly complex airspace, and using adaptive contingencies to manage normal and non-normal operations. These changes compel development of new and emerging capabilities that enable innovative ways for humans to interact with data and manage information. Increasing complexity of AAM corresponds with use of predictive modeling, data analytics, machine learning, and artificial intelligence to effectively address known hazards and emergent risks. The roles of humans will dynamically evolve in increments with this technological and operational evolution. The interfaces for how humans will interact with increasingly complex and assured systems designed to operate autonomously and how information will need to be presented are important challenges to be resolved.

Keywords: In-time Safety, Data Analytics, Human-Autonomy Teaming

1 Evolution of the National Airspace System (NAS)

As today's National Airspace System (NAS) rapidly expands with new and evolving aviation markets, a major challenge facing safety in design and operational assurance is how humans will interact with increasingly autonomous systems. The increasing complexity of design and operations includes a wider mix and higher density of flying vehicles integrated with today's traditional aircraft and human operators managing ever-increasing flight information through dynamic interfaces for in-time identification, assessment, and mitigation of safety risks.

The evolution in the aviation markets involves introduction of different types of operations with an ever-widening array of aircraft from traditional passenger jets and General Aviation aircraft to new electric vertical takeoff and landing (eVTOL) vehicles. eVTOLs are designed and built by original equipment manufacturers (OEMs) and brought into service by traditional and entrepreneurial operators (e.g., airlines, cargo carriers, first responders, companies operating in the electronic commerce space, and air taxis). The Federal Aviation Administration (FAA) in its Vision 2035 described a concept aligning future airspace design that could accommodate different operational missions and vehicle performance characteristics for safe and efficient flight [1].

At the same time, the National Aeronautics and Space Administration (NASA) is envisioning and researching new concepts for how these types of operations could be integrated to work together as part of Advanced Air Mobility (AAM) [2]. The different domains comprising AAM are shown in Figure 1. One emerging domain is urban air mobility (UAM) with its new and adaptive airspace, innovative vehicles, and other operational features [3]. UAM operates in low altitude airspace with vehicles carrying passengers and cargo between takeoff and landing sites that in some cases are called vertiports [4].

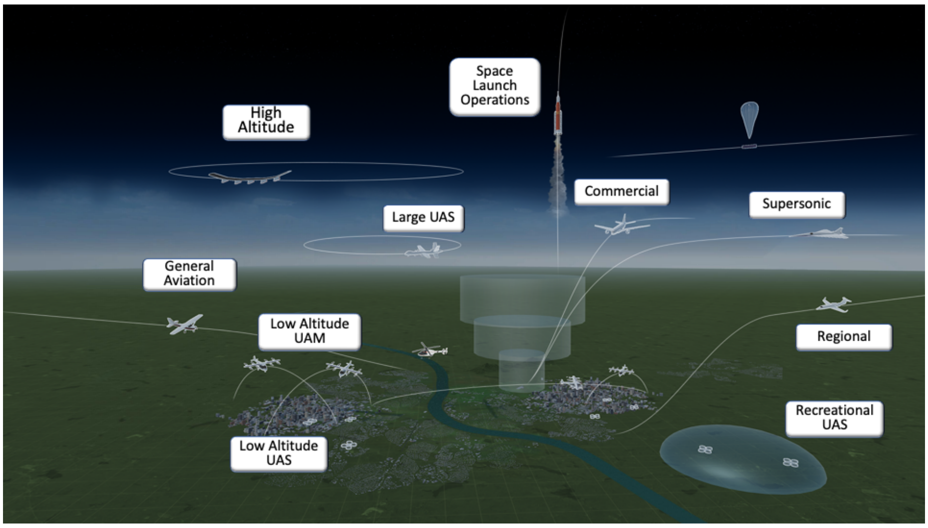

Fig. 1. AAM domains.

These concepts pose potential new critical safety challenges and risks with novel types of aircraft flying among traditional aircraft and helicopters, having frequent flights each day, within close proximity of one another carrying people and cargo, and in more congested and operationally complex airspace. This technological and operational evolution will be accompanied by changes in the roles of human operators. The interfaces designed for how humans will interact with increasingly complex and assured systems that operate semi-autonomously/autonomously and how information will need to be managed, accessed, presented, and acted on by humans are key considerations to assure that the in-time safety risks properly assessed and mitigated.

1.1 Addressing the New Safety Challenges

The need for a new and evolving paradigm to address the safety challenges in AAM was identified by the National Academies [5, 6]. They recommended an In-time Aviation Safety Management System (IASMS) to address risks in-time by focusing on integrating real-time risk monitoring, assessment, and mitigation with a more responsive time frame for detecting known risks and identifying emergent risks and latent patterns in safety trends. An IASMS will necessarily evolve over time as new automation systems are integrated in the NAS, which will require the roles of humans and automation to evolve accordingly in order to assure aviation safety.

IASMS will evolve to bridge today's safety management system (SMS) and the faster operations in AAM. The IASMS provides in-time risk monitoring, assessment, and mitigation in a manner that overcomes the brittleness of the current FAA system that will not scale according to how AAM will grow in complexity. The need for IASMS is compelled by the public having a low tolerance for aviation incidents and accidents, which has resulted from aviation's very high level of safety, as well as the importance of addressing regulatory shortcomings (e.g., the Boeing 737 MAX accidents [7]). FAA SMS regulations and advisory materials have significantly contributed to safety improvements. Prior to SMS, safety was emphasized such as with the expression of flying like you train and training like you fly, which flowed across key aspects of flying as Aviate, Navigate, and then Communicate.

To move toward the envisioned AAM future, NASA has been developing an IASMS concept of operation (ConOps) that builds from traditional commercial and other aviation operations and scales with the increasing complexity of new emerging and evolving operations across AAM domains [8, 9]. The IASMS ConOps is under the NASA Strategic Implementation Plan Thrust 5, called In-Time System-Wide Safety Assurance, that builds out adaptive in-time safety threat management. The IASMS features fully integrated hazard detection and risk assessment capabilities that can invoke trusted methods for dynamic, multi-agent planning, evaluation, execution, and monitoring of in-time risk mitigating response to safety hazards.

The safety risks addressed by IASMS are shown as an operational view in Figure 1 [8]. IASMS is enabled by three higher-level functions of Monitor, Assess, and Mitigate that involve domain-specific safety monitoring and alerting tools, integrated predictive technologies with domain-level applications, and in-time safety risk management.

IASMS builds on conceptual and notional Services, Functions, and Capabilities (SFCs) that together enable the dynamic Monitor, Assess, and Mitigate functions with closely coupled interdependencies that are unique to the IASMS [9]. A safety risk that emerges during the life cycle phases of design or operations explains why a service is required to manage it. A service is useful for preventing or trapping a safety risk before harm can occur. A service could be provided by the vehicle, UAM system, and/or another agent in the architecture. A function represents what action is required by automation, automated systems, pilots, and other human operators. A function can integrate streams of information and data to ascertain what should be done and when to mitigate a risk as well as use predictive analytics to identify and project known and emerging trends from performance data. A capability involves how a particular risk type would be addressed by technology, including sensors and models that will detect, generate, validate, and distribute information and data across network architectures and be used by functions and services to monitor, assess, and mitigate those risks. The risks included in the operational view in Figure 1 are shown in Table 1 with corresponding examples of SFCs and risk mitigations. SFCs could be distinguished as operational or safety, and an operational SFC may be used for safety, i.e., an operational SFC could be related to and inform risk monitoring, assessment, and mitigation to assure a safety margin or establish new ones. Example SFCs represent prototype models and techniques developed by NASA to demonstrate features and analyze model performance and test assumptions.

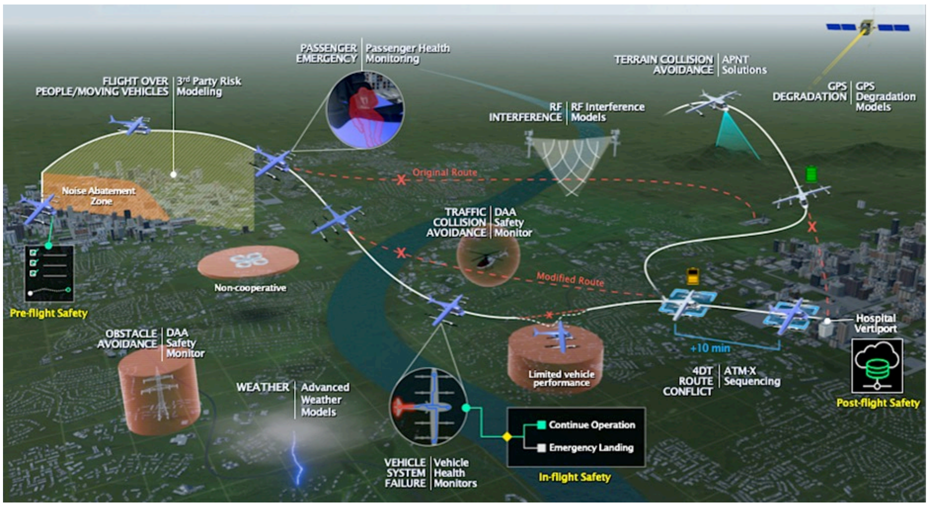

Fig. 2. IASMS operational view.

Table 1. IASMS safety risks, SFCs, and mitigations.

Safety Risks	Monitoring, Assessment, and Mitigation	Example SFCs
Flight Over People/ Moving Vehicles	Vehicle maintains safe lateral and vertical distances around people and moving vehicles as established in its flight plan or as information is updated during flight, e.g., changes to route of flight	3rd Party Risk Modeling; cellular telephone data,

	or 3rd party risk assessment. If the risk cannot be reduced below threshold, then vehicle dwells in place until the risk subsides, flies a different route to the destination, returns home, or flies to another location.	public events monitoring
Obstacle Avoidance	Flight plan accounts for known obstacles as specified on aeronautical charts and maps, and other geographic information products to ensure safe lateral and vertical distances. DAA systems monitor planned operational trajectory to detect unanticipated obstacles to be avoided. In certain airspace, all vehicles use DAA.	Detect and Avoid (DAA) Safety Monitor
Weather	Flight plan checked before departure for current and forecast weather including temperature, wind direction, strength and gust, convective weather, precipitation, and icing. Microweather forecasting for urban flight planning. Pilot weather reports used to update flight plan. In-flight monitoring and assessment. If severe weather cannot be avoided in-flight, then vehicle dwells in place until the risk subsides, flies a different route to the destination, returns home, or flies to another location.	Advanced Weather Models
Radio Frequency (RF) Interference	Operational systems monitor and assess RF interference for disrupting communications. If mitigation fails, then vehicle dwells in place until the risk subsides, flies a different route to the destination, returns home, or flies to another location.	RF Interference Models
Global Positioning System (GPS) Degradation	Operational systems monitor and assess the quality of the GPS signal. If mitigation fails, then vehicle dwells in place until the risk subsides, flies a different route to the destination, returns home, or flies to another location.	GPS Degradation Models
Vehicle System Failure	Vehicle health monitoring systems continuously assess status and performance of on-board operational systems (e.g., battery power and propulsion performance). In case of failure, assesses hazard volume and emergency landing locations.	Vehicle Health Monitors
Traffic Collision Avoidance	An on-board real-time operational system provides detect-and-avoid warning, determines maneuvers away from other airborne vehicles, and executes these maneuvers while communicating with other vehicles and Unmanned Aircraft System (UAS) Service Supplier (USS).	DAA Safety Monitor
Terrain Collision Avoidance	An on-board real-time operational system provides detect-and-avoid warning and maneuvering away from terrain to avoid controlled-flight-into-terrain (CFIT).	Alternative Positioning, Navigation, and Timing (APNT) Solutions

Route Conflict	On-board and/or ground-based operational systems provide safe sequencing and spacing between flights going/leaving the same destination verti-port/airport, as well as separation between vehicles having crossing trajectories including during climb/descent. In-flight monitoring and assess-ment. Risk mitigated in-flight through trajectory modification.	Air Traffic Management – eXploration (ATM-X) Sequencing and Spacing

The IASMS will evolve to deliver a progression of SFCs that can assure safety as operations grow increasingly complex. The transformative changes in envisioned future aviation systems will necessitate new and emerging capabilities that enable innovative ways for humans to interact with data and manage information as cognitive requirements evolve. Complexity entails a multiplicity of dimensions with expected and unanticipated interactions. One depiction of these different dimensions is shown in Figure 2.

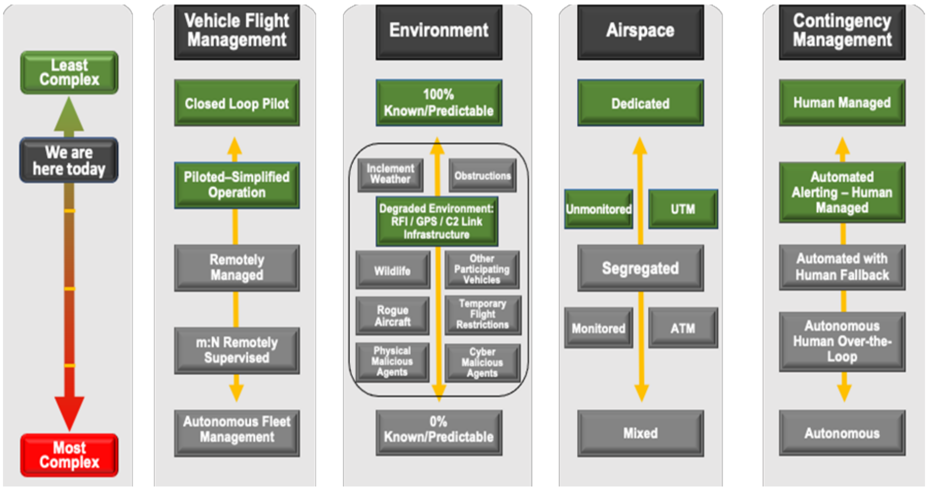

Fig. 2. Example factors of complexity.

SFCs involve data and information that contribute to what is referred to as safety intelligence. Safety intelligence can be considered knowledge of parameters of safety performance and issues gained through the analysis of available data and learning that enables improvements to safety management including risk management, safety assurance, and safety promotion activities [10].

The high level of safety in today's commercial operations has been achieved through the growth of safety intelligence by OEMs, commercial airlines, FAA, and others. The National Transportation Safety Board (NTSB) is recognized internationally for its vital work in identifying the causal and contributory factors of past aviation accidents and incidents, which is referred to as reactive safety or Safety I. Reactive safety provides intelligence of causal and contributory factors for what went wrong. The transition to proactive safety intelligence emphasizes the proactive detection of emergent risks that

do not readily fit the patterns of causal factors of past accidents and incidents. Proactive analysis may identify unusual patterns or weak signals before accidents or incidents can occur [11]. Proactive analysis also identifies intervening action taken by the human to prevent or mitigate a hazard before it can cause an accident or incident and "save the operation," which is referred to as Safety II. Safety II emphasizes what the human does right in preventing or mitigating a risk during an operation. Progression of safety intelligence combines Safety I and II and integrates predictive analytics of future safety problems. Predictive models interpret data for future trends that could lead to unsafe conditions. These reactive, proactive, and predictive aspects of safety intelligence, as shown in Figure 3, involve different types of information and data fusion as well as the dynamics of how humans interact and use that information.

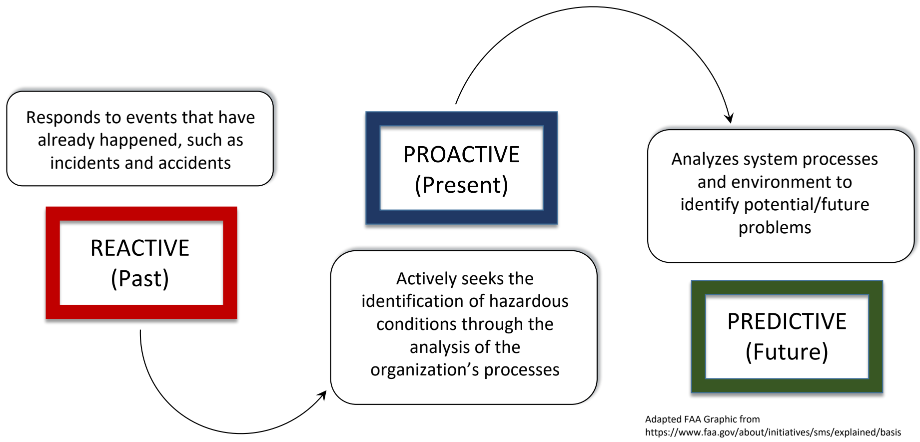

Fig. 3. Progression of safety intelligence.

2 HIMI Challenges

The IASMS provides risk management and safety assurance in a manner substantially more responsive in addressing known and emerging risks than with today's SMS. The FAA SMS regulation pertains to commercial airline carriers certificated under 14 CFR Part 121 and does not currently apply to any other category of aircraft operation. These other categories include helicopter operators (including medical transport), General Aviation, small Unmanned Aircraft Systems (sUAS) and commercial operators of smaller aircraft with limited passenger and cargo capability. IASMS would bring these and other AAM domains under its umbrella. To achieve a broader approach to risk management and safety assurance, the IASMS utilizes system-wide data that are aggregated and fused across the heterogenous data architectures belonging to the different commercial airline operators and other operators, although standards may require commonalities in architectures to provide appropriate, compatible, and consistent alerting and mitigation strategies.

A key thesis is that in the end state of AAM and during transformations to that end state, ensuring the safety of flight through separation provision will continue to be the responsibility of a separation provision service (such as a federated UAS Service Supplier relative to today's FAA air traffic control (ATC) service), a user (e.g., pilot), or an automated system. As shown in Figure 4, in today's operations the pilot is responsible for ensuring safety of flight in flight conditions called Visual Flight Rules (VFR) and the FAA ATC service is responsible during flight conditions called Instrument Flight Rules (IFR). In the event of an accident or incident, either the pilot or the ATC service would be accountable for safety assurance with no division of responsibility between the two. In the future, assured automation may have responsibility for safety of flight for certain AAM operations [12]. Across these AAM transformations the roles of the human, separation service provider, and automation will change, e.g., changes to the pilot's role might be characterized as on-the-loop or over-the-loop (oversight role). In a fully assured autonomous operation the role of the human may be outside the mission operation and instead the human would be more of a system administrator monitoring the systems and handling outages and other technical administrative responsibilities. This poses critical challenges on the human exerting authority over and teaming with automation including bi-directional communication between the pilot and automation [13]. Transitioning to automation being fully responsible under VFR and IFR flight conditions requires development of new certification standards for safety assurance and other considerations.

	Flight Rules		
Responsibility for Safety of Flight	**VFR**	**IFR**	**AAM**
Human Pilot	Today	–	–
Service Provider	–	Today	–
Automation	Future Assured System?	Future Assured System?	Future Assured System

Fig. 4. Flight rules for safety of flight.

Being more responsive means the IASMS can scale for different operational positions with increasingly complex information being acted upon using more streamlined decision-making processes. A pilot flying on-board the aircraft represents a level of complexity that is well-understood in today's operations. A pilot remotely flying multiple vehicles using automated systems for certain critical risks such as Detect-and-Avoid (DAA) would necessitate different informational needs for the higher level of complexity. An operator working as a dispatcher controlling a fleet of highly autonomous vehicles flying different missions has unique informational needs and task complexity that can be specific to each operation. A safety manager and data analyst assessing post-flight vehicle performance data, safety reports, maintenance data, and other data sources may have other informational and data requirements. These are notionally shown in Figure 5.

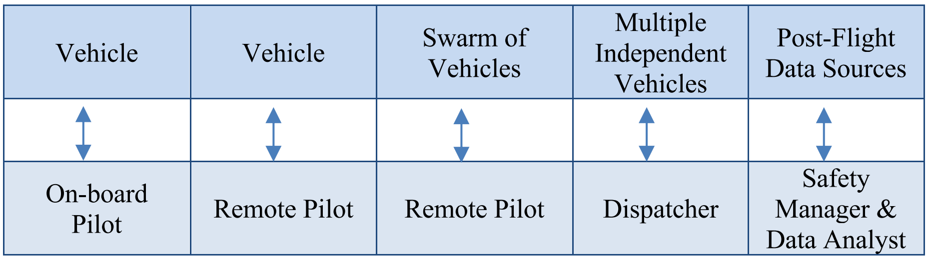

Fig. 5. Notional operational positions.

These processes entail fewer human decision-makers who each have the right knowledge at their level and who can trust the automated system. It provides information to humans monitoring operations in a manner to keep the humans attentive to the information and make off-nominal situations apparent.

A key attribute of an IASMS is that it supports the human to quickly manage known operational risks through highly automated information systems that integrate SFCs across operators and federated architectures. SFCs would be distributed amongst on-board the vehicle, ground-based, and the cloud using digital twins for increased system reliability. These information systems would collect, aggregate, fuse, model, and distribute data that are used by IASMS functions.

3 Information Requirements

The information requirements for IASMS used by humans and automated systems can be organized according to 16 information classes as shown in Figure 6 [14]. Each class of information is comprised of data parameters, for example, the information class of geo-spatial constraints involves data parameters of airspace boundaries, no-fly zones such as temporary flight restrictions, obstacles (type, location, extent), terrain, and operator-defined geofenced areas as stay-in regions.

Fig. 6. Classes of IASMS information.

Safety functions for highly autonomous operations monitor and assess these data for risks. Standards would establish minimum performance requirements for the quality of digital data. Data quality considerations include availability, latency, update rates, integrity, security, formats, implementation and service costs, bandwidth utilization, and standards [15].

The information class of safety reports includes data parameters from investigations of past accidents and incidents, and vetted reports from pilots and air traffic controllers about other safety concerns. Data sources of safety reports include the NASA Aviation Safety Reporting System (ASRS), Aviation Safety Action Program (ASAP), FAA Air Traffic Safety Action Program (ATSAP), Mandatory Occurrence Reporting System (MORS), Pilot Reports (PIREPS) about weather conditions, error and failure logs for equipment and functions, and maintenance logs including the age and history of critical components. These data sources are used today by different domains of the NAS and would be updated for UAM and urban UAS.

IASMS collects and fuses these data to monitor and detect known patterns of safety risk. An IASMS quickly identifies unknown risks that are different from recognized anomalies, precursors, and trends such as based on exceedances, latent safety risks not readily apparent, and emergent or unknown patterns [8, 9].

The potential for emergent risk necessitates innovative data analytical solutions involving machine learning and artificial intelligence (ML/AI) that can distinguish between proactive methods, that build on precedent, and predictive methods that currently are not resident or have limited application for commercial aviation SMS. These methods will involve human interaction to provide learning data during development and to provide a real-time interface with the AI at intermediate autonomy levels. A proactive SMS has the objective to identify precursors and anomalies and their likely causal

factors that may lead to hazardous operations as posed through data markers and system behaviors. A proactive SMS attempts to preemptively mitigate the event before it manifests as an unsafe condition.

Predictive SMS derives from the International Civil Aviation Organization (ICAO) with its Annex 19 and Document 9589 that call for SMS to evolve to take advantage of advances in big data analytics with predictive analysis of safety indicators [16]. Outcomes of this approach are improved organizational processes and activities leading to faster collaborative decision-making, modelling and predicting of future operations and enhanced safety intelligence. Predictive SMS intends to take mitigating action based on the potential risk as determined from applying predictive analytics to normal operational data (i.e., not accident data) to reduce the risk of an accident that has not yet happened; to identify safety issues that have not yet occurred but probably will happen if left unaddressed; and to act based on actionable data including updating risk control strategies. Predictive safety management attempts to identify all possible risks in different scenarios based on both observed but also hypothesized situations to anticipate future risk controls, risk mitigation options, safety assurance, and organizational needs. Importantly, predictive SMS is complementary to and not a replacement for reactive and proactive SMSs. That is, all three SMSs represent important safety management approaches intended to work collectively and in an integrated manner to enhance aviation safety.

Lastly, an IASMS quickly informs system design as emergent risks are identified to establish effective risk controls to be enacted "in-time." In this context, an emergent risk was not identified during the design phase such as in hazard risk analysis or flight testing. When a risk is identified during operations, that information needs to loop back to design engineers to assess whether there might be a systemic flaw, perturbation, unforeseen condition, or other hidden risk that requires mitigation involving a change to equipment, systems, and/or procedures and training.

New and emerging capabilities are enabling new ways for humans to interact with data that have not been possible before. To achieve the objectives, the human's roles and responsibilities are envisioned to transform in pace with the equally transformative changes required to achieve the future aviation vision.

4 HIMI Design Considerations

Design of Human Interfaces and Management of Information (HIMI) will be critical to successful deployment of an IASMS. The interface with safety management data and information is the key portal through which human operators maintain situation awareness and team with increasingly autonomous systems for safety assurance and in-time risk management.

For example, traditional roles and responsibilities of pilots, dispatchers, and air traffic controllers as done today by these different professionals may blend into a single hybrid position simultaneously managing multiple flights, but with significantly more trustworthy decision aids and assured autonomous SFCs.

Challenges for the teaming of humans with automated systems correspond with the maturity needed for autonomy and complexity of the operation. Further, teams can exhibit emergent behavior and develop new structures and properties in more complex arrangements and across a larger range of missions, which provide opportunities to improve task delegation, decision making, and problem solving. Increasing complexity can result from and in turn drive the need for new group and machine learning capabilities as well as new collaborative modeling techniques. These challenges have a direct effect on how information would be managed and the human interface to it [17, 18]. Examples of these challenges include:

- Pilots successfully manage equipment malfunctions that occur in normal operations but insufficient system knowledge, flight crew procedure, or understanding of aircraft state may decrease their ability to respond to failure situations. This is a particular concern for failure situations which do not have procedures or checklists, or where the procedures or checklists are incomplete or have limited applicability.
- Pilots sometimes rely too much on automated systems and may be reluctant to intervene, and auto flight mode confusion errors can occur, for example, programming and usage errors with the aircraft Flight Management System.

Much of what is known today about humans teaming with automation is exemplified in the design and operation of aircraft flight management systems and automated and driver-assisted automobiles. One question is to what extent will standards, guidance, and lessons learned be extensible to the design of more complex teaming arrangements. For safety assurance, extensibility builds on trustworthy decision support, mitigation of bias in ML/AI systems, and operator proficiency [19, 20].

4.1 Trustworthy Decision Support with IASMS

Safety information analyzed and communicated over advanced AAM architectures pose a challenge of integrating IASMS SFCs with operational SFCs. For example, operational SFCs manage traffic flow within a corridor using 4-dimension trajectories for effective spacing between vehicles while safety SFCs perform Detect-and-Avoid ensuring strategic separation between vehicles that perform traffic flow management and collision avoidance to handle tactical separation with other vehicles and aircraft. Teaming of humans and automation includes consideration of developing shared experience to develop mutual trust. This experience enables calibrating understanding and expectations of how team members will perform across a range of operations and constraints [19].

4.2 Systemic Bias in IASMS

Systemic bias poses a challenge in the way algorithms analyze information and identify risk mitigations. AI bias occurs when the use cases and data used to train algorithms contain deviations not representative of normal operations. Considering that ML/AI systems can be opaque in which the parameters and models may not be easily understood by humans, these biases may not be detected.

4.3 Operator Proficiency with IASMS

Current guidance for flight deck systems and an understanding of design shortcomings provides an important framework in the design of automated systems. HIMI implications include ensuring flight mode awareness as part of an emphasis on flight path management, such as reducing the number and complexity of modes from the pilot's perspective and improving the feedback to pilots on mode transitions. Other factors for considerations include energy state awareness and skill degradation resulting from use of automated systems.

5 Data Analytics for In-time Safety

As IASMS data becomes increasingly more available, a challenge is how to support humans through trustworthy decision support in the context of substantially increased number of available data streams, volume of data, and more complex and nuanced factors that may impact operational safety. Today, safety managers and boards typically review these data sequentially in stovepipes. Only a small fraction of available safety data is analyzed and those that are mined often have time latencies in event occurrence, assessment, and any mitigation actions.

Transitions to in-time data analytics will fuse data to identify known precursors, anomalies, and trends, as well as emergent risks more quickly and effectively. This poses important challenges for the design of a system that can simultaneously leverage these data streams while teaming in ways that support the needs of the human decision maker. Data analytics can be applied to operational data that go beyond techniques used with current safety management and reactive and proactive SMS, to enable in-time predictive risk assessment, mitigation, and safety assurance. New SFCs for "in-time" tools and predictive data analytics could isolate existing and emergent patterns of underutilized, underexploited, and unidentified system-wide data types to inform the IASMS. An important consideration is that the data management system and how the information will be used by the human has to be considered from the initial IASMS design in ways that enable teaming paradigms that support the needs of the human decision maker. A human-centric approach would utilize innovative methods, procedures, and techniques to safely design, integrate, implement, and validate a human-system integrated IASMS capable of providing accessible system-wide predictive data analytics, effective "in-time" risk mitigation and safety assurance, and learning from all operations.

The complexity of the human interface with data analytics expands with the complexity of safety SFCs. Predictive SMS involves faster safety decision-making, accurate modelling and predicting future outcomes, and enhanced safety intelligence. Safety risks may appear as validated concerns known to designers and operators and known to be detected and mitigated by assured SFCs. Emergent risks may be unknown to designers and operators (e.g., an unexpected and surprising situation masked by unidentified but actionable data markers) with SFCs designed and developed to understand, adapt, and manage them through machine learning or artificial intelligence. Other risks could be recognized by designers or operators as potential latent safety risks even though these are outside the envelope for assured SFCs to detect and mitigate them.

Lastly, there could be unforeseen risks that are not recognizable by designers or operators or by safety assurance SFCs and await discovery.

6 Integration of ML/AI in IASMS

As automated systems make use of machine learning and artificial intelligence to handle big data, the underlying algorithms will evolve in sophistication. This may exceed what humans are able to understand if HIMI is not considered early in the system design lifecycle of IASMS development. Research has shown the difficulties experts have in understanding the "black box" methods of neural networks and some other advanced data analytical capabilities. While pilots could be considered users and partners with automated systems, they will need a level of expertise with system design, which corresponds with the complexity of an operation, to understand performance requirements and limitations, interdependencies, and other considerations in operational and safety SFCs.

Human decision makers will be trained to trust a system and to the extent needed for their operation have knowledge and skill with how underlying algorithms work. Similarly, automated systems will need to be designed for an appropriate level of transparency through HIMI so the human can maintain situation awareness and possibly anticipate how risk is monitored, assessed, and mitigated. Designing for that level of transparency will be a significant challenge for IASMS due to its basis in ML/AI-enabled data analytics, for which some frequently used techniques are inherently opaque. Human-centered design of HIMIs, comprehensive human-system integration approach, and dedicated operator training on these systems are key to IASMS success.

HIMI is an important part of the path for assuring the safety performance of automated systems with the human monitoring and verifying/validating how data are analyzed, risks identified, and mitigations prioritized and executed. ML/AI would be used to intercede and disrupt the sequence of causal and contributing risk factors and better and more quickly inform system design as emergent hazards are identified as necessary to establish effective risk controls. Design parameters may be initially set for known operational considerations and constraints, but these parameters could also be configured to manage emergent unknowns that could occur. Part of the challenge in identifying patterns is the extensibility of models to interpret data to identify different emergent patterns that appear similar to but yet are different from known patterns.

Longer time frames using data from IASMS services may have implications to better inform needed or required changes to other parts of the aviation SMS. This could include, for example, changes in pilot training programs, flight procedures, equipment design, or the content of scheduled maintenance checks. As IASMS data analytics expands with the ever-increasing volume of disparate data, the path to predictive SMS is challenged by the need for data analytics that can evaluate and detect unknown vulnerabilities and discover precursors, anomalies, and other predictive indicators, as compared to more traditional safety metrics used such as exceedances in nominal flight data values and trends from the Flight Operations Quality Assurance (FOQA) program. These vulnerabilities are "needles in a haystack" that ML/AI methods can discover. Data analytics would use SFCs that fuse and integrate different types of information

and present it using innovative displays and interfaces used by the human as part of human-autonomy teaming (HAT) for in-time assessment and decision-making.

Some ML/AI research has focused on the problems of anomaly detection and precursor identification in heterogeneous, multivariate, variable-length time series datasets within the aviation safety domain. This includes examining flight operational data sets, such as FOQA, where data objects are flights consisting of multivariate time series that include sensor readings and pilot inputs. One goal has been to detect anomalous flight segments that may represent potential unknown vulnerabilities. NASA has developed three algorithms for this task: the semi-Markov switching vector autoregressive model (SMS-VAR—jointly with the University of Minnesota), the Multiple Kernel Anomaly Detection (MKAD) algorithm, and a deep learning-based algorithm that can use prelabeled anomaly data if available. NASA has found these algorithms to be complementary and expects that future IASMS will use and integrate multiple algorithms to leverage their relative strengths [21, 22, 23].

7 Use of Human-Autonomy Teaming in IASMS

HAT is expected to be a cornerstone for operator information requirements that supports development and use of design guidance. These information requirements will shape HIMI as well as procedures and training to avoid misuse, disuse, or abuse of interactions.

Today's baseline for HAT takes form that includes the aircraft Flight Management System (FMS) comprised of systems having varying levels of automation and it has been suggested that some 20% of normal flights necessitate the pilot taking action to handle malfunctions and other off-nominal conditions. It has also been suggested that only 10% of flights are completed based on the original flight plan entered into the FMS before departure.

Leading edge work with HAT considers the multiple approaches that provide viable solutions for teaming. New and different HIMI standards and guidelines may need to be developed and existing guidance updated to support the information requirements of an IASMS [24]. Some examples of these strategies include the following [25]:

- Playbook represents an organized pre-planned set of action plans that can be used as a checklist identifying what needs to be done and who has responsibilities for completing them, with options addressing specific circumstances of the situation.
- Terms of engagement that represent stepwise shifts toward increased use of automation. Automation could be purely advisory with the operator performing the action, to the automation identifying the action but allowing time for the operator to review and possibly override or change the action, to conditions under which automation automatically executes the action and may inform the human afterwards [26].
- Predictive timelines inform the operator about how the automation is monitoring and assessing the future environment and the mitigations that may be required to improve operator situation awareness and decision making.

- Flight trial planning used by the operator to assess "what if" changes to flight plans and viability of contingency management strategies.

Hurdles need to be overcome for autonomous systems to be effectively integrated. These include brittleness, perceptual limitations, hidden biases, and lack of a model of causation important for understanding and predicting future events [19]. At the same time, human use of complex automation can be constrained by poor understanding of what the automation is doing, high workload when trying to interact with AI systems, poor situational awareness, and performance deficits when intervention is needed, biases in decision making based on system inputs, and degradation of manual skills. To overcome these challenges the human must understand and predict the behaviors of the AI system, develop appropriate trust relationships with it, make accurate decisions based on input received from the system, and be able to exert control over the system in a timely and appropriate manner.

These challenges can be organized as a series of overarching higher-level HAT research questions for focusing on IASMS, as follows [27]:

- Teaming models: What models of multi-agent interaction best fit or align with multiple human roles in IASMS, and how should this fit be assessed?
- Shared situation models: Considering that IASMS has different users working on different timelines to assure different parts of safety, how can a common architecture be defined from network architectures (e.g., ground, air, cloud) with their respective SFCs to support a common knowledge base?
- Trust calibration: How can inter-agent trust be appropriately built, calibrated, and leveraged to establish roles, authority, and transitions of control? Steps toward defining an envelope of trust could include development of a detailed use case for a particular mission that would lead to system requirements for automated systems and operational requirements for development of procedures and training.
- Contingency management: How is the IASMS designed so that human-machine teams retain or improve upon current capabilities to identify, assess, and mitigate known risk and detect emergent risk such as from new or different patterns in performance data?
- Performance measurement: How can the IASMS measure performance of human-machine teams and identify improvements to system performance?
- Paths to operational approval: What are the contributions of IASMS to certification and operational approval of human-machine teaming concepts?

Teaming paradigms correspond with the tasks of the human shifted to automated systems. Humans are still expected to have critical safety analyst roles in the future aviation SMS up through the design and operation of an automatically assured fully autonomous monitoring, detection, and risk mitigation SMS.

8 Cognitive Engineering with ML-AI and HAT

As the aviation system transforms with AAM and the different safety assurance methods become more complex, integration of cognitive engineering with ML/AI and HAT raises a range of concerns about HIMI. These concerns are framed as questions including the following:

- Where are opportunities possible for new types of interactions and how might they reveal knowledge gaps in the design path for IASMS?
- How should best practices be leveraged?
- How should information be scaled for display and how should the human operator navigate through menus and other techniques for more details?
- How should safety dashboards be tailored for information requirements of different users?
- How should time critical information be pushed to the display even if it interrupts whatever was being displayed at that time?
- How much training and education should be required relative to the level of understanding needed of the underlying algorithms?

Transparency of AI behavior could be accomplished in real-time through effective visualizations of explanations of the detected risks and identified mitigations. These explanations would need to adapt to the skill level of the human that would consider their prior knowledge and experience as well as performance level such as fatigue [19]. Bias can be introduced in AI systems during development of algorithms, development of training sets, and decision biases. As bias effects the performance of the AI system, over time it can affect the human operator in managing risk information. Processes and methods will be used in the design, testing, verification, and validation of evolving AI systems to detect AI blind spots and edge cases.

9 Data Visualization

Data visualization is important for aligning what, how, when, and why humans use safety data and their interactions with the information from automated systems. Data visualization scales from low complexity with the human pilot flying on-board or remotely operating a single vehicle using a ground control station. At higher levels of data visualization complexity, the data architecture expands through data delivered to the human pilot remotely managing a swarm of synchronized vehicles or multiple vehicles having asynchronous missions. The data architecture would expand with an interface with a federated air traffic management system involving other operators participating in the exchange of data through common services. Other types of data in the architecture having intersections with risk management include current and forecast weather, reports of weather conditions from pilots, geographic information systems data such as obstructions, airspace configuration such as temporary flight restrictions, corridor data such as congestion and slot management, and safety margins.

Data visualization represents the portal through which the human pilot or fleet manager develops and maintains situation awareness. The paradigm of the human pilot seated on the flight deck looking at aircraft controls and displays and out the window for other traffic is overtaken by the human looking at displays presenting different types of data. For example, data visualization for the fleet manager would be different from today's pilot looking at the cockpit display of traffic information (CDTI). Similarly, data visualization would be different from today's air traffic controller looking at the "radar" situation display. Data visualization as part of the design of an IASMS and HAT would involve a portfolio of decision-maker-centric strategies and innovative collaborative human interface techniques integrating data streams across distributed architectures while enabling modular and flexible approaches that meet operational requirements and respect and preserve operator-specific knowledge and skills.

10 Summary and Conclusions

Rapid changes to the NAS pose significant challenges to the design of HIMI for safety assurance in operations and design. Safety in design and operational safety assurance are critical factors for how humans will interact with increasingly autonomous systems. Future concepts for AAM pose potential new critical safety risks with novel types of aircraft and other vehicles having different performance capabilities flying in increasingly complex airspace and using adaptive contingencies to manage normal and non-normal operations. The roles of humans will dynamically evolve with this technological and operational evolution. The interfaces for how humans will interact with increasingly complex and assured systems designed to operate autonomously and how information will need to be presented to assure in-time safety, are important challenges to be resolved.

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References

1. MITRE Corporation: The Future of Aerospace: Interconnected from Surface to Space. FAA Managers Association Managing the Skies 18(1), 12-15 (2020).
2. Verma, S., Monheim, S., Moolchandani, K., Pradeep, P., Cheng, A., Thipphavong, D., Dulchinos, V., Arneson, H., Lauderdale, T., Bosson, C., Mueller, E., and Wei, B.: Lessons Learned: Using UTM Paradigm for Urban Air Mobility. In: 39th Digital Avionics Systems Conference (DASC), Virtual Event (2020).
3. Federal Aviation Administration: Unmanned Aircraft Systems (UAS) Traffic Management (UTM) Concept of Operations v2.0. FAA, Washington, DC (2020).
4. Patterson, M., Isaacson, D., Mendonca, N., Neogi, N., Goodrich, K., Metcalfe, M., Bastedo, B., Metts, C., Hill, B., DeCarme, D., Griffin, C., and Wiggens, S.: An Initial Concept for Intermediate-State, Passenger-Carrying Urban Air Mobility Operations. In: AIAA Sci Tech (2021).

5. National Academies of Sciences, Engineering, and Medicine: In-time Aviation Safety Management: Challenges and Research for an Evolving Aviation System. The National Academies Press, Washington, DC (2018). Retrieved from https://doi.org/10.17226/24962.
6. National Academies of Sciences, Engineering, and Medicine: Advancing Aerial Mobility: A National Blueprint. The National Academies Press, Washington, DC (2020). https://doi.org/10.17226/25646.
7. U.S. Department of Transportation Office of Inspector General: Weaknesses in FAA's Certification and Delegation Processes Hindered Its Oversight of the 737 MAX 8. Report No. AV2021020. Washington, DC (2021).
8. Ellis, K., Krois, P., Koelling, J., Prinzel, L., Davies, M., and Mah, R.: A Concept of Operations and Design Considerations for an In-time Aviation Safety Management System (IASMS) for Advanced Air Mobility (AAM). In: AIAA Sci Tech (2021).
9. Ellis, K., Krois, P., Koelling, J., Prinzel, L., Davies, M., Mah, R., and Infeld, S.: Defining Services, Functions, and Capabilities for an Advanced Air Mobility (AAM) In-time Aviation Safety Management System (IASMS). In: AIAA Aviation (2021).
10. Daeschler, R.: The need for Safety Intelligence based on European safety data analysis. In: OPTICS Workshop (2015). http://www.optics-project.eu/optics1/wp-content/uploads/2015/04/04_R-Daeschler_The-need-for-Safety-Intelligence-based-on-European-safety-data-analysis_OPTICS-2nd-Workshop.pdf.
11. Ellis, K., Krois, P., Mah, R., Koelling, J., Prinzel, L., Davies, M., and Infeld, S.: An Approach for Identifying IASMS Services, Functions, and Capabilities. In: IEEE Digital Avionics Systems Conference (2021).
12. Bradford, S.: Foundation – Global Air Traffic Management Concept of Operations, ICAO Document 9854, Panel on Operational Sustainability in an Increasingly Congested and Heterogeneous Airspace. In: SCI TECH Forum, Virtual Event: AIAA (2022).
13. Lachter, J., Hobbs, A., and Holbrook, J.: Thinking Outside the Box: The Human Role in Increasingly Automated Aviation Systems. In: International Symposium on Aviation Psychology (2021). https://ntrs.nasa.gov/citations/20210011929.
14. Young, S. Ancel, E., Moore, A., Dill, E., Quach, C., Foster, J., Darafsheh, K., Smalling, K., Vasquez, S., Evans, E., Okolo, W., Corbetta, M., Ossenfort, J., Watkins, J., Kulkarni, C., and Spirkovska, L.: Architecture and Information Requirements to Assess and Predict Flight Safety Risks During Highly Autonomous Urban Flight Operations. National Aeronautics and Space Administration Langley Research Center, Hampton, VA (2020). NASA/TM-2020-220440. https://ntrs.nasa.gov/citations/20200001140.
15. American National Standards Institute: Standardization Roadmap for Unmanned Aircraft Systems, Version 1.0 (2018).
16. International Civil Aviation Organization: Safety Management, Standards and Recommended Practices–Annex 19. In: Convention on International Civil Aviation, 2nd Edition. ICAO: Montreal (2016).
17. Flight Deck Automation Working Group: Operational Use of Flight Path Management Systems. Performance-based operations Aviation Rulemaking Committee/ Commercial Aviation Safety Team (2013). https://www.faa.gov/aircraft/air_cert/design_approvals/human_factors/media/oufpms_report.pdf.
18. Federal Aviation Administration: Summary of the FAA's Review of the Boeing 737 MAX. FAA, Washington, DC (2020). https://www.faa.gov/foia/electronic_reading_room/boeing_reading_room/media/737_RTS_Summary.pdf.
19. National Academies of Sciences, Engineering, and Medicine: Human-AI Teaming: State of the Art and Research Needs. The National Academies Press, Washington, DC (2021). https://nap.edu/26355.

20. Wojton, H., Sparrow, D., Vickers, B., Carter, K., Wilkins, J., and Fealing, C.: DAAWorks2021: Characterizing Human-Machine Teaming Metrics for Test and Evaluation. Institute for Defense Analyses (2021). https://www.ida.org/-/media/feature/publications/d/da/dataworks-2021-characterizing-human-machine-teaming-metrics-for-test-and-evaluation/d-21564.ashx.
21. Das S., Matthews, B., Srivastava, A., and Oza, N., Multiple Kernel Learning for Heterogeneous Anomaly Detection: Algorithm and Aviation Safety Case Study, Proceedings of the SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD-2010), pp. 47-56, 2010., doi:10.1145/1835804.183513.
22. Melnyk, I., Banerjee, A., Matthews, B., and Oza, N., Semi-Markov Switching Vector Autoregressive Model-Based Anomaly Detection in Aviation Systems, Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD), 2016.
23. Memarzadeh, M., Matthews, B., and Avrekh, I., Unsupervised Anomaly Detection in Flight Data Using Convolutional Variational Auto-Encoder, Aerospace, Vol. 7, p.115 doi:10.3390/aerospace7080115.
24. Federal Aviation Administration: Avionics Human Factors Considerations for Design and Evaluation. AC No: 00-74. FAA, Washington, DC (2019). https://www.faa.gov/documentLibrary/media/Advisory_Circular/AC_00-74.pdf.
25. Brandt, S., Lachter, J. B., Russel, R., Shively, R. J.: A human-autonomy teaming approach for a flight-following task. In: Baldwin C. (eds.) Advances in Neuroergonomics and Cognitive Engineering. AHFE Advances in Intelligent Systems and Computing, vol 586, 12–22. Springer, Cham (2017).
26. Parasuraman, R., Sheridan, T. B., & Wickens, C. D.: A model for types and levels of human interaction with automation. In: IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans, 30 (3), 286-297 (2000).
27. Holbrook, J. B., Prinzel III, L. J., Chancey, E. T., Shively, R. J., Feary, M. S., Dao, Q., Ballin, M. G., & Teubert, C.: Enabling urban air mobility: Human-autonomy teaming research challenges and recommendations. In: AIAA AVIATION Forum, Virtual Event: AIAA (2020).